REPORT DOCUMENTATION PAGE

AFRL-SR-AR-TR-04-

0390

1. REPORT DATE *(DD-MM-YYYY)*
01-09-2003

2. REPORT TYPE
Final Report

3. DATES COVERED *(From - To)*
31AUG03 - 31 MAY04

4. TITLE AND SUBTITLE
Unified Collection and Coordination for UCAVs:

Final Progress Report

5a. CONTRACT NUMBER
F49620-01-C-0031

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

6. AUTHOR(S)

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8. PERFORMING ORGANIZATION REPORT NUMBER
N/A

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Air Force Office of
Scientific Research Room 713
4015 Wilson Blvd.
Arlington VA 22203

10. SPONSOR/MONITOR'S ACRONYM(S)
AFOSR/NM

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT
Distribution is unrestricted.

20040810 016

13. SUPPLEMENTARY NOTES

14. ABSTRACT
LMTS and SSCI are conducting a research program aimed at the problem of managing swarms of autonomous, self-reconfiguring swarms of intelligent sensors and weapons. Our goal is a theoretically comprehensive but also potentially practical unification of the two major aspects of the problem: Multi-Agent Collection (i.e., distributed robust data collection, fusion, and interpretation of often poorly characterized or poorly-defined data) and Multi-Agent Coordination (i.e., distributed robust platform/sensor monitoring and control). Data fusion/correlation and sensor/platform management is a control theory problem in which the underlying entities (targets, sensors, data, platforms) are stochastically varying multi-object systems. This necessitates a practical unification of control theory and point process theory. LMTS developed a potentially tractable approach to multisensor, multitarget sensor management. This approach uses approximate multitarget filters (a probability hypothesis density (PHD) filter or a multiple-hypothesis correlator (MHC) filter) as the underlying multitarget filter/predictor, and "natural" probabilistic objective functions (e.g. posterior expected number of targets.) combined with a "maxi-PIMS" optimization strategy for tractably hedging against unknown future observations. The approach was extended to multi-step look-ahead, sensors with non-ideal dynamics (e.g. UAVs), sensors without directly observed states, and communications drop-outs.

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF: Unclassified			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			Dr. John Sjogren
Unclassified	Unclassified	Unclassified	Unlimited Distribution	9	**19b. TELEPHONE NUMBER** *(include area code)* 703-696-6564

7-29-04

May 28, 2004

"Unified Collection and Coordination for UCAVs"

Final Report

Submitted to: Air Force Office of Scientific Research

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UNIFIED COLLECTION AND COORDINATION FOR UCAVs

AFOSR Contract F49620-01-C-0031
Progress Report for 2003

Principal Investigator: Ronald P.S. Mahler, Ph.D.
Lockheed Martin Tactical Systems (**LMTS**)
Eagan, Minnesota

1. OBJECTIVES

The problem of managing swarms of autonomous, self-reconfiguring sensors and weapons divides into two general realms: *Multi-Agent Collec*tion (i.e., distributed robust data fusion and data interpretation) and *Multi-Agent Coordination* (i.e., distributed robust platform and sensor monitoring and control). The sensors on the various autonomous platforms must try to collect and interpret data from targets of interest, in the right places at the right times. In turn, the platforms must try to properly re-configure and position themselves to accomplish mission objectives based on this data, also in the right places at the right times. Ideally, these two processes should be connected by a feedback loop in which some platforms may be re-configured in order to improve the over-all quality of data be collected on certain targets. Consequently, data fusion/interpretation and platform configuration/control cannot be separated, since one function cannot be accomplished successfully without the other. Under this Cooperative Control Theme 2 contract, Lockheed Martin Tactical Systems (LMTS) of Eagan MN and its subcontractor Scientific Systems Co., Inc. (SSCI) of Woburn MA pursued technologies aimed at unification of Multi-Agent Collection and Multi-Agent Coordination. Our approach has been based on a potential unification of innovative distributed hybrid-systems control theory with a new multisensor-multitarget statistics called "finite-set statistics" (FISST). FISST is a version of (multi-dimensional) point process theory that has been specifically tailored to facilitate solution of multi-platform, multi-sensor, multi-target problems.

Multi-Agent Coordination. The overall objective of the proposed research in *Multi-Agent Coordination* was to develop efficient tools for the analysis and synthesis of hybrid control systems. Specifically, LMTS and SSCI developed: (1) a mathematical programming framework for hybrid systems analysis and synthesis, (2) a computational hybrid control paradigm, (3) transition-aware anytime algorithms for time-bounded synthesis, and (4) suitable modeling and cooperative control of UAV swarms.

Multi-Agent Collection. The overall objective of the proposed research in *Multi-Agent Collection* was to develop effective new approaches for the collection, fusion, and interpretation of multitarget observations, using sensors onboard or offboard coordinated swarms of UAVs. As part of this effort, LMTS and SSCI (1) developed a new theoretical approach for integrating multiplatform, multisensor, multitarget sensor management into Multi-Agent Coordination; (2) investigated the use of real-time Bayes nonlinear filtering in detecting, tracking, and identifying targets obscured by low signal-to-noise sensing conditions; (3) developed new approaches to robust data fusion; (5) devised a method for avoiding some of the computational difficulties

associated with hybrid systems; and (6) showed how to encompass more general inference techniques such as Bayesian statistics, the Dempster-Shafer theory of evidence, and fuzzy logic.

2. STATUS OF EFFORT

This is the final report for the project. It describes research completed since the last interim report submitted on August 17 2003, under a previously negotiated six-month no-cost extension. Previously we investigated the detailed statistics and mathematics of control-theoretic objective functions for multisensor-multitarget sensor (and platform) management, assuming ideal sensor dynamics. The emphasis of the final phase of our research has been to relax the assumption of ideal sensor dynamics, thus generalizing our approach to UAVs. Our work currently encompasses the following aspects of sensor management:

- targets of current or potential tactical significance;
- multistep look-ahead (control of sensor resources throughout a future time-window);
- sensors with non-ideal dynamics, including sensors residing on moving platforms such as UAVs;
- sensors whose states are observed indirectly by internal actuator sensors; and
- possible communication interference.

Our approach also addresses a more subtle issue: *the impossibility of deciding between an infinitude of plausible objective functions*, by concentrating on "probabilistically natural" sensor management goals.

Nevertheless, our work still has significant limitations. We must assume that the sensors are fixed in number. This precludes the possibility of sensors entering or leaving a scenario. We must assume that each platform carries exactly one sensor. Our basic scheme is still centralized. Any future basic research work in this area must address such issues.

In addition, we have investigated (1) a potential approximate multitarget filtering approach based on a multitarget extended Kalman filter (EKF); and (2) a design for sensor management based on a joint multisensor-multitarget particle-systems approximation.

3. ACCOMPLISHMENTS

In what follows we describe the research completed since August 2003. In section 3.1 we describe our basic sensor management approach and the basis for its potential implementation using two approximation techniques: the probability hypothesis density (PHD) filter and the multi-hypothesis correlator (MHC) filter. Sections 3.2 and 3.3 are devoted to our concluding efforts. In section 3.2 we describe a potential implementation using joint multisensor-multitarget particle system methods. In section 3.3 we describe a fourth approximation technique, based on the concept of a multitarget extended Kalman filter (EKF).

3.1 Sensor management based on PHD and MHC approximations. Sensor management is inherently an *optimal nonlinear control problem.* Sensor management differs from standard control applications, however, in that it is also inherently a *stochastic multi-object problem.* It

involves *randomly varying sets of targets*, *randomly varying sets of sensors/sources*, *randomly varying sets of collected data*, and *randomly varying sets of sensor-carrying platforms*. Our work under this project has pursued a theoretically foundational but potentially practical control-theoretic basis for multisensor-multitarget sensor management using the following system-level, Bayesian paradigm:

- model all sensors and targets as a single joint dynamically evolving multi-object stochastic system;
- propagate the state of this system using a multisensor-multitarget Bayes filter;
- apply objective functions that express global probabilistic goals for sensor management;
- apply optimization strategies that hedge against the inherent unknowability of future observation-collections;
- devise principled approximations of this general (but usually intractable) formulation.

The last step is crucial and difficult: devise principled, potentially tractable: (1) multitarget filters; (2) global objective functions; and (3) optimization strategies. It requires finite-set statistics (FISST), a novel random-set version of point process theory. Our work now encompasses the following aspects of sensor management:

- targets of current or potential tactical interest;
- multistep look-ahead (control of sensor resources throughout a future time-window);
- sensors with non-ideal dynamics, including sensors residing on moving platforms such as UAVs;
- sensors whose states are observed indirectly by internal actuator sensors; and
- possible communication interference.

Our approach also addresses a more subtle issue: the impossibility of deciding between an infinitude of plausible objective functions, by concentrating on "probabilistically natural" sensor management goals.

Nevertheless, our work still has significant limitations. We must assume that the sensors are fixed in number. This precludes the possibility of sensors entering or leaving a scenario. We must assume that each platform carries exactly one sensor. Our basic scheme is still centralized. Any future basic research work in this area must address such issues.

Our objective function of greatest interest, the posterior expected number of targets (PENT), is constructed using a new optimization strategy, "maxi-PIMS," that optimizes the likelihood of collecting the predicted ideal measurement-set (PIMS). Intuitively speaking, in a PIMS there are no false alarm/clutter observations, every target in the FoV generates an observation, and target-generated observations are noise-free.

The PENT objective function is used in conjunction with approximate multitarget filters: the probability hypothesis density (PHD) filter or the multi-hypothesis correlator (MHC) filter. Preliminary simulations using PENT with an MHC filter have demonstrated good sensor management behavior.

In more detail: Our core approach, based on multitarget posterior distributions, was introduced in March 1996 and slightly generalized in 1998. Assume that sensors are known and fixed in number. Let $\mathbf{x}^* = (\mathbf{x}^{*1},\ldots, \mathbf{x}^{*s})$ be the concatenation of their state vectors. Regard all targets and sensors as part of a single stochastically evolving system with joint state $(X, \mathbf{x}^*)$. Propagate this system using a joint recursive Bayes filter:

$$f_{k+1|k}(X,\mathbf{x}^*) = \int f_{k+1|k}(X,\mathbf{x}^* \mid W,\mathbf{w}^*)\cdot f_{k|k}(W,\mathbf{w}^*)\delta W$$

$$f_{k+1|k+1}(X,\mathbf{x}^*) = \frac{f_{k+1}(Z_{k+1} \mid X,\mathbf{x}^*)\cdot f_{k+1|k}(X,\mathbf{x}^*)}{f_{k+1}(Z_{k+1})}$$

where

$$f_{k+1}(Z) = \int f_{k+1}(Z \mid X,\mathbf{x}^*)\cdot f_{k+1|k}(X,\mathbf{x}^*)\delta X$$

The joint Markov transition

$$f_{k+1|k}(X,\mathbf{x}^*|W,\mathbf{w}^*) = f_{k+1|k}(X,\mathbf{x}^*|W,\mathbf{w}^*,\mathbf{u}_k)$$

actually depends on a joint control vector $\mathbf{u}_k = (\mathbf{u}_k^1,\ldots,\mathbf{u}_k^s)$ that influences the future joint sensor state $\mathbf{x}^*_{k+1}$. Consequently, the joint multisensor-multitarget posterior distributions $f_{k|k}(X,\mathbf{x}^*)$ implicitly depend on a time-sequence of control vectors. We have suppressed this dependence to keep notation simpler.

The core mathematical concept of our approach is the probability generating functional (p.g.fl.). The p.g.fl.'s

$$G_{k|k}[h] = \int h^X f_{k|k}(X)\delta X$$

$$G_{k+1|k}[h] = \int h^X f_{k+1|k}(X)\delta X$$

contain the same information as the predicted and updated multitarget posterior distributions $f_{k+1|k}(X)$ and $f_{k+1|k}(X)$. So we should instead concentrate on objective functions defined in terms of the posterior p.g.fl. $G_{k+1|k+1}[h]$. Since it depends on the unknown future observation-set Z_{k+1} we must hedge against this fact. We could produce a hedged p.g.fl. $\dot{G}_{k+1|k+1}[h]$ by taking the expectation of $G_{k+1|k+1}[h]$ over all observation-sets, but $\dot{G}_{k+1|k+1}[h]$ no longer has any dependence on the unknown control/future sensor state. The expectation of some nonlinear transform of $G_{k+1|k+1}[h]$ no longer has this problem, but will be intractable. Intractability results if we use a maxi-min approach, i.e. assume that the worst-possible observation-set has been collected. Previously we studied a more tractable "maxi-null" approach that turned out to be too conservative. So we devised a new "maxi-PIMS" strategy.

To understand PIMS, assume that sensor likelihood functions have the form

$$L_{\mathbf{z}}(\mathbf{x}) = f_{k+1}(\mathbf{z} \mid \mathbf{x},\mathbf{x}^*_{k+1}) = f_{\mathbf{W}_{k+1}}(\mathbf{z} - \eta_{k+1}(\mathbf{x},\mathbf{x}^*_{k+1}))$$

Abbreviate $\eta(\mathbf{x}) = \eta_{k+1}(\mathbf{x}, \mathbf{x}^*_{k+1})$. Begin by assuming that the future sensor FoV is a cookie-cutter: $p_D(\mathbf{x}, \mathbf{x}^*_{k+1}) = \mathbf{1}_S(\mathbf{x})$ where $\mathbf{1}_S(\mathbf{x}) = 1$ if $\mathbf{x} \in S$ and $\mathbf{1}_S(\mathbf{x}) = 0$ otherwise. That is, an observation will be collected from a target if it is in the FoV, but not otherwise. Assume that some multitarget state estimation process has been used to estimate the number $\hat{n}$ and states $\hat{\mathbf{x}}_1,...,\hat{\mathbf{x}}_{\hat{n}}$ of the predicted tracks. Then an "ideal" noise- and clutter-free observation at time-step $k+1$ would be

$$Z_{k+1} = \bigcup_{\hat{\mathbf{x}}_i \in S} \{\eta(\hat{\mathbf{x}}_i)\}$$

If the FoV is not a cookie cutter then we must account for the fact that p_D can have values between zero and one. Define the subset $S_a(p_D)$ of single-target state space by

$$S_a(p_D) = \{\mathbf{x} |\, a \leq p_D(\mathbf{x})\}$$

where we abbreviate $p_D(\mathbf{x}) = p_D(\mathbf{x}, \mathbf{x}^*_{k+1})$. Let A be a uniformly distributed random number on [0,1]. Then the random subset $\omega \rightarrow S_{A(\omega)}(p_D)$ can be regarded as a *random FoV* that selects among a range of possible alternative cookie-cutter FoVs, whose shapes are specified by $p_D(\mathbf{x})$. This random set contains the same information as $p_D(\mathbf{x})$ since $p_D(\mathbf{x})$ can be recovered from it: $\Pr(\mathbf{x} \in S_a(p_D)) = \Pr(A \leq p_D(\mathbf{x})) = p_D(\mathbf{x})$. Also, note that $E[\mathbf{1}_{S_A(p_D)}(\mathbf{x})] = p_D(\mathbf{x})$ where "E[-]" is expected value.

Using the PIMS, we produce a hedged posterior p.g.fl. $\dot{G}_{k+1|k+1}[h]$. The posterior expected number of targets (PENT) objective function $\dot{N}_{k+1|k+1}$ can be defined in terms of it. Maximizing $\dot{N}_{k+1|k+1}$ results in *single-step look-ahead* sensor management—we select an optimal control only for the next time-step. In *multistep look-ahead* we determine optimal controls for a future time-window. Special techniques are required to deal with this.

Suppose now that we approximate the multitarget filter using a probability hypothesis density (PHD) filter or a multi-hypothesis correlator (MHC) filter. Then we can derive closed-form formulas for objective functions such as PENT defined in terms of $\dot{G}_{k+1|k+1}[h]$. Once we have such formulas, they are used in conjunction with an approximate filter for sensor management. In single-step look-ahead we determine the next joint control vector (or joint sensor state) by optimizing the objective function. Collect the future observation-sets and use the predictor and corrector of the approximate filter to incorporate this new information. Repeat. Similarly for multistep look-ahead, except that controls/sensor states are chosen for a window, and the approximate filter is operated for all steps in that window.

3.2 Sensor management based on particle-systems approximation. The PHD and MHC approximations have specific realms of application appropriateness. The MHC filter can, as it already is, be used in conventional applications. The PHD filter can be used in highly stressing applications in which the numbers of targets and sensors is larger and when, for example, signal-to-noise ratio (SNR) is relatively small. It would be useful to have an approximation that can deal with smaller SNRs—with the tradeoff that numbers of targets and sensors must also be smaller if tractability is to be achieved. Under this research we investigated the application of

particle-system (a.k.a. sequential Monte Carlo) approximations to the sensor management approach previously described. In order for particle-system approximation to be effective, it must be applied not just to the multitarget state space but to the entire joint multisensor-multitarget system. That is, any joint multisensor-multitarget particle is a joint multisensor-multitarget state-set

$$\breve{X} = \{\mathbf{x}_1, ..., \mathbf{x}_n, \mathbf{x}_1^*, ..., \mathbf{x}_{n^*}^*\}$$

where n is the number of targets; n^* is the number of sensors; $\mathbf{x}_1, ..., \mathbf{x}_n$ are the states of the individual targets; and where $\mathbf{x}_1^*, ..., \mathbf{x}_{n^*}^*$ are the states of the individual sensors. A joint multisensor-multitarget Bayes filter

$$f_{k+1|k}(X, X^*) = \int f_{k+1|k}(X, X^* \mid W, W^*) \cdot f_{k|k}(W, W^*) \delta W \delta W^*$$

$$f_{k+1|k+1}(X, X^*) = \frac{f_{k+1}(Z_{k+1} \mid X, X^*) \cdot f_{k+1|k}(X, X^*)}{f_{k+1}(Z_{k+1})}$$

is used to propagate the evolving joint state-set; this filter is approximated using particle methods; and the PENT objective function is applied to this approximation. A preliminary version of the filter has been implemented in a simple two-dimensional scenario.

3.3 Sensor management based on multitarget EKF. Conventional single-sensor, single-target control is based on optimization of objective functions applied to the extended Kalman filter (EKF). In essence, the EKF is based on expansion of logarithms of the Markov transition density $f_{k+1|k}(\mathbf{y}|\mathbf{x})$ and likelihood function $f_{k+1}(\mathbf{z}|\mathbf{x})$ in Taylor's series around suitable operating points; and then truncating these series after the quadratic term. This is possible because the state variables $\mathbf{y}, \mathbf{x}$ are continuous and because $f_{k+1|k}(\mathbf{y}|\mathbf{x})$ and $f_{k+1}(\mathbf{z}|\mathbf{x})$ are often differentiable in $\mathbf{y}, \mathbf{x}$. It could be useful to extend such approximations to the multisensor-multitarget realm, by expanding the logarithms of multitarget Markov densities $f_{k+1|k}(Y|X)$ and multisensor-multitarget likelihood functions $f_{k+1}(Z|X)$ in Taylor's series. This is not possible because multisensor-multitarget systems are hybrid (i.e., mixed continuous-discrete) systems—the multitarget state-sets Y, X involve both continuous variables (individual state variables) and a discrete variable (the number n of states). So, multisensor-multitarget systems are not only non-differentiable. Worse, as hybrid systems they are very computationally challenging.

Under this research, we showed how to render Y, X fully continuous by rendering the number n of targets a continuous variable. We showed how to generalize conventional multisensor-multitarget observation and motion models to continuous state-sets X. We showed how to generalize conventional differential calculus to functions of X and, from there, how to expand such functions in Taylor's series. This leads to potential EKF-type approximations of the general multisensor-multitarget filter. These approximations can then be used with the sensor management approach previously described.

4. PERSONNEL SUPPORTED

1. Ronald Mahler, Ph.D., Lockheed Martin MS2 Tactical Systems, P.I.

2. John R. Hoffman, Ph.D., Lockheed Martin MS2 Tactical Systems

5. TECHNICAL PUBLICATIONS

5.1 Journal Publications

1. (invited paper) R. Mahler (2004) "'Statistics 101' for Multisensor, Multitarget Data Fusion," *IEEE AES Mag., Part 2: Tutorials*, 19(1): 53-64, 2004.
2. R. Mahler (2003) "Multitarget Filtering via First-Order Multitarget Moments," *IEEE Trans. AES*, 39(4): 1152-1178, 2003.
3. R. Mahler and J. Hoffman (2004) "Multitarget Miss Distance via Optimal Assignment," *IEEE Trans. SMC-Part A* 34(3): 327-336, 2004.

5.2 Reviewed Conference Proceedings

1. (invited keynote paper) R. Mahler (2004) "Random sets: Unification and computation for information fusion—a retrospective assessment," In *Proc. 8th Intl. Conf. on Inf. Fusion*, Stockholm, Sweden, June 28-July 1, 2004, Intl. Soc. Inf. Fusion, Sunnyvale, CA, 2004.
2. R. Mahler (2005), "Multitarget sensor management of dispersed mobile sensors," in D. Grundel, R. Murphey, and P. Pardalos, eds., *Theory and Algorithms for Cooperative Systems*,in in S. Butenko, R. Murphey, and P. Paralos (eds.), *New Developments in Cooperative Control and Optimization*, World Scientific, to appear, 2005.
3. R. Mahler (2004) "Sensor management with non-ideal sensor dynamics," *Proc. 7th Int'l Conf. on Inf. Fusion*, Stockholm, June 28-July 1, 2004.

6. INTERACTIONS/TRANSITIONS

6.1 Conference Presentations

1. R. Mahler (2004) "Target preference in multitarget sensor management: A unified approach," in I. Kadar, ed., *Sign. Proc., Sensor Fusion, and Targ. Recog. XIII*, SPIE (Vol. 5429), Bellingham WA, 2004.
2. R. Mahler and T. Zajic (2004), "Probabilistic objective functions for sensor management," in I. Kadar, ed., *Sign. Proc., Sensor Fusion, and Targ. Recog. XIII*, SPIE (Vol. 5429), Bellingham WA, 2004.
3. A. El-Fallah, M. Perloff, B. Ravichandran, R.Mehra, R. Mahler, T. Zajic, and C. Stelzig (2004) "Multitarget sensor management with target preference," in I. Kadar, ed., *Sig. Proc., Sensor Fusion, and Targ. Recog. XIII*, SPIE (Vol. 5429), Bellingham WA, 2004.

6.2 Technology Transitions

Technology developed under this contract (specifically, multisensor, multitarget sensor management via multi-hypothesis trackers) has led to a Phase II SBIR from AFRL/SNAT and a Phase I SBIR from AFRL/IFEA:

Project Title: Representation for Enhanced Sensor Exploitation. *Funding Agency*: AFRL/SNAT Dayton OH/Mr. Martin Eilders (937-904-9273). *Contract*: F31615-03-M-1511. *Contract Type*: SBIR Phase I (prime contractor, Scientific Systems Company Inc.). *Performance Period*: 06/04-05/06. *Description*: SSCI and its subcontractor LMTS will be developing a new approach to multi-platform, multi-sensor, multi-target sensor management. The approach is based on principled approximations of a control-theoretic scheme based on "natural" control-theoretic objective functions. The kick-off meeting was held on May 19 2004.

Project Title: Sensor Management for Improved Situation Awareness. *Funding Agency*: AFRL/IFEA Rome NY/Dr. Mark Alford (???). *Contract*: F8750-04-C-0114. *Contract Type*: SBIR Phase I (prime contractor, Scientific Systems Co. Inc.). *Performance Period*: 05/04-04/05. *Description*: SSCI and its subcontractor LMTS will be developing approaches for sensor management in support of Levels 2 and 3 data fusion (situation and threat assessment), potentially including sensors carried by UAVs and surveillance platforms such as J-STARS. The approach is based on incorporation of Tactical Significance Maps into principled approximations of a control-theoretic scheme. The kick-off meeting was held on May 25 2004.

7. PATENT DISCLOSURES

None.

8. HONORS

1. On April 3 2004 Dr. Ronald Mahler was one of 50 Lockheed Martin MS2 2004 Premium Circle award winners, and one of two Lockheed Martin MS2 2004 Author of the Year awards. Lockheed Martin Maritime Surveillance and Sensors (MS2) employs 12,000 people and consists of the following major Lockheed Martin sites: Moorestown NJ, Manassas VA, Syracuse NY, and St. Paul MN.
2. Dr. Ronald Mahler published an invited tutorial paper on his finite-set statistics (FISST) approach in *IEEE Aerospace Systems Magazine Tutorials*.
3. Dr. Ronald Mahler will be one of three invited plenary speakers at the Seventh International Conference on Information Fusion, to be held in Stockholm, Sweden, in June 2004. This conference is the major international conference devoted exclusively to information fusion.
4. In April 2004 Dr. Ronald Mahler served on an invited panel of data fusion experts at the 2004 SPIE Defense and Security Symposium, Orlando. The panel addressed outstanding or misunderstood problems and approaches in data fusion.
5. In June 2004 Dr. Ronald Mahler will serve on an invited panel of data fusion experts at the 2004 International Conference on Information Fusion, Stockholm. The panel will address outstanding issues in higher-level fusion (sensor/resource management and threat and situation assessment).